Linking on LinkedIn:
An Empirical Analysis of Job Search using Online Social Networks

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ABSTRACT

Both labor economists and social scientists have previously presented that social connections (like friends and family) are valuable in a job search process. In the past, social connections, usually categorized as strong and weak ties, were limited by the modes of communication. The recent growth of online social networks has enabled job seekers to stay connected with all of their acquaintances, peers, friends, and family. Thus the number of online connections – weak or strong – that an individual is able to manage has increased significantly. In this paper, we first examine if an individual's social network plays a role in driving their job search behavior not only on social network but also on other modes. Secondly, we examine how the ties (weak and strong) and search intensity affect the job outcomes (which we model sequentially; job leads, interviews and offers) of online social networks vs. those from other job search modes like career fairs & agencies, newspapers & magazines, internet, and close friends and family (offline). Using a survey data of 109 users, we first build an economic model of search behavior with structure cost and benefit functions. We then estimate the model to recover some key estimates. We find that users with more strong ties search more on all modes. However, users with more weak ties search more on online social networks. Doubling the number of weak connections translates to about one hour/week increase in search intensity. We also find that weak ties are especially helpful in generating job leads but it is the strong ties which play an important role in generating job interviews and job offers. Doubling weak ties leads to additional one job leads from online social networks. We also find that effect of online strong ties usually extends to outcomes on other modes. However, effect of online weak ties is limited to outcomes from online social networks.

1 INTRODUCTION

"How to effectively search for jobs?" is an enormously important question for individuals, firms and policy makers. Governments around the world spend millions in trying to train and find jobs for unemployed individuals. Over the last 4 decades job seekers have modified their job search efforts as the technology has shaped this process. According to Monthly Labor Review of 1973 (Bradshaw 1973) 71 percent job seekers reached out to the employers directly, 40 percent reached out to agencies (public or private), 14 percent used their formal and information social connections to search for jobs. This changed slightly in 1991 (Bortnick and Ports 1992) when job seekers reached out to 22 percent of their friends and family. Growth of Internet since late 90's has reshaped this again because of the growth of Internet based firms (like Monster.com) who specialize in matching individuals with firms.

A key element in job search process has been the role of individuals' social connections. There is significant literature that suggests that "who you know" plays a very important role in someone finding a job. (Granovetter 2005) argues that social networks are valuable because they affect the flow and quality of information, reward or punish connections, and improve the trust and confidence on the information. These factors are especially important because online platforms have enabled a much larger competition amongst the job seekers as every job post is now available to every job seeker across the globe. According to a survey conducted by CareerBuilder.com[1] in 2009, each job post received over 75 resume. Social connections could potentially help job seekers in reaching directly to hiring managers and improve their probability of visibility (from 1 in 75) because of trust on quality of information shared by the common connection.

Growth of Internet and broadband has led to a meteoric rise in online social networking firms like Facebook which allows users to connect with their friends. We are still grappling with the impact of Facebook on our society. There is a lot of work which examines different aspects of social networks and how it affects various individual and collective outcomes (Ellison, Steinfield,

[1] http://www.theworkbuzz.com/get-the-job/job-search/companies-receive-more-than-75-resumes-on-average-for-open-positions/

and Lampe 2007; Valenzuela, Park, and Kee 2009). However, most social networking sites (SNS) have unique characteristics and thus all are not used for job search. There are online social networking sites like LinkedIn which have grabbed a lion's share in this space. A recent cover-page article in Fortune magazine (Hempel 2010) suggested that connecting on LinkedIn is more useful than exchanging business cards or churning resumes. Online social networks are gaining popularity because of their extensive reach and simplified usability by internet users. Based on statistics from Alexa.com (November 2010), the more popular job search boards (like monster.com or indeed.com) are used by approximately 0.25% of internet population each spending on average 4 minutes on these websites. However, online social (or professional) networks surpass these numbers by a factor of 10. Similar statistics from Alexa (November 2010) show that LinkedIn is consumed by 3.4% of daily internet users each spending on an average 7.4 minutes/day. According to LinkedIn (November 2011), one new member is joining the portal every second with a current user-base of over 100 million people in 200 countries. Employers are responding to this growth by positioning, advertizing and using their employees' social network as a way to recruit potential employees.

A fundamental difference in online social networks, compared to users' formal and information network is the ability of individuals to maintain and manage far more online connections - average number of friends on facebook.com[2] is 130. However, most of users' network consists of what one calls "weak ties" (Granovetter 1973). This raises the question about the effectiveness of these online professional networks in the job search process. Too many connections may be helpful, but they may also make it harder for user to search for jobs effectively. Similarly, employers may also realize that a large number of irrelevant connections are not useful in measuring the social capital of an individual.

It is also not clear if unemployed users consider online social networks a great tool for job search. After all, unemployment information is not something users may be willing to share with their network especially when the network consists of large number of weak ties. So users may be reluctant to conduct directed search on these networks.

[2] http://www.facebook.com/press/info.php?statistics

In summary, while there is a lot of hype and press surrounding online social networks, there is little empirical work that has examined this issue in any detail. This paper seeks to examine two major questions:

(i) How are people allocating their job search efforts across different modes, especially, online social networks? How does users' online social network (including weak ties) affect these search efforts?

(ii) Are online networks effective in generating job offers? Does users' online social network affect this effectiveness? How do strong and weak ties influence job leads vs. job interviews and offers?

Answers to these questions require having access to some detailed data on users' job search behavior. To do this, we administer a survey to unemployed users asking them detailed questions on their job search methods, their online and offline social capital, and job outcomes. We then provide a model of users' job search behavior and effectiveness of search modes, especially emphasizing the role of social capital.

Using completed survey of 109 users, we find that job seekers with larger number of connections on online social network (LinkedIn in this case) spend more time searching for jobs on that platform. This additional time on online social networks gets re-allocated from the time spent search for jobs on the Internet. We also find that "strength of weak-ties" and "strength of strong-ties" arguments hold for online social networks but under different job outcomes. Weak-ties continue to help job seekers find new job leads whereas the strong-ties help in converting these job leads to offers. One interesting finding is that a large number of weak-ties tend to reduce the strength of strong-ties implying that job seekers should not be driven by the hype around online social networks to grow their network beyond a manageable state. In other words, a much larger network size might help job seeker find new leads but will hurt them when seeking help from their strong connections in converting those leads to offers.

We believe our paper is important on several dimensions. First, whole domain of online social networks and job outcomes is ripe for serious empirical work. How new online platforms are reshaping job search process and its effectiveness is enormously important question for labor economists, sociologists and technologists. The answer to our research questions are of importance to individuals who are searching for jobs and firms like LinkedIn whose business models depend on answers to these questions. More importantly, even policy makers (especially Department of Labor) who spend significant resources on training users and employers on how to efficiently find a match, would find our research important and useful. Second, we collect a unique and detailed data set. Very little empirical work with a particular focus on online networks has been possible due to lack of detailed data. Despite some limitations of our survey, we believe our paper will be able shed some light on questions largely unanswered due to data unavailability. We hope that our work will pave the road for many promising future studies, which undoubtedly are needed to investigate this very important issue.

This paper is organized as follows. We provide a literature review in section 2. In section 4, we provide some details on our data and survey including summary statistics. We build a simple model of user job search which provides a way for empirical estimation in section 3. We present out results and analysis in section 5. Finally we conclude with a discussion of implications of our results, limitations and future possibilities in section 6.

2 LITERATURE

We draw from two major literatures. First is job search literature in labor economics. Scholars have studied labor market and the role of social ties on the job outcomes (Granovetter 1983) (Holzer 1988), wages (Montgomery 1992), and job information diffusion (Granovetter 1995). It has been shown in the past that the number of job leads converting to job offers is highest for search through friends and family and direct job applications (Holzer 1988). In a study of recruitment process of a bank, the role of social networks was found to be positive and significant (Petersen, Saporta, and Seidel 2000). At the same time the role of social ties was found to be positive and significant on wage over time (Rosenbaum et al. 1999).

Differentiating between the unemployed and employed workforce, researchers have found that the job search while being employed is more effective when compared to the job search when unemployed (Blau and Robins 1990). An analytical work using the diffusion of job lead information through network structure suggests duration dependence of unemployment (Calvó-Armengol and Jackson 2004).

As pointed in a recent review (Mouw 2006), estimating the role of social capital has been increasingly challenging due to homophily (McPherson, Smith-Lovin, and Cook 2001) and reflection (Manski 1993). He suggests that an investigation of social capital on job search intensity was overlooked, which was an important component in determining if online social capital really helps in labor market. Extant literature is also found to be prone to endogeneity problems (Durlauf 2002). Some have also argued that there may be no significant value in informal social channels when compared to other channels (Lin 1999).

The second literature we explore is the economics and sociology literature examining the role of social capital. Seminal work in the area of sociology originated from the mid-twentieth century (Katz and Lazarsfeld 1955); (Coleman, Katz, and Menzel 1957)(Mansfield 1961); (Merton 1968); (Van den Bulte and Lilien 2001)(Valente 2003) with a larger emphasis on product marketing or innovation diffusion. During the same time the origination of strength-of-weak-ties theory (Granovetter 1973) changed the perspective of social capital. Granovetter suggested that friends & family being close to an individual do not contribute to the discovery of a newer content (job leads in his study), but it is the weak-ties (people who we know but do not communicate with on a regular basis) that provide a larger volume of novel information. It was later shown that both strong and weak ties play a role in product and information diffusion (Goldenberg, Libai, and Muller 2001) but may have a different impacts based on the interaction between the ties and the size of the network. It was also shown that strong ties are important (Krackhardt 1992) in causing actual changes whereas weak-ties may lead to more diffusion of information. This may suggest that weak ties may be useful in generating job leads but strong ties help more in getting the final job offers. At the same time studies on structural-holes (Burt 1995) showed that the position in network matter more than the tie-strength. Overall, the idea is that networks cause an increased effect on the diffusion of information (Economides and Himmelberg 1995), but the true role of peer influence may be hard to estimate from the observational data because of reflection problem (Manski 1993).

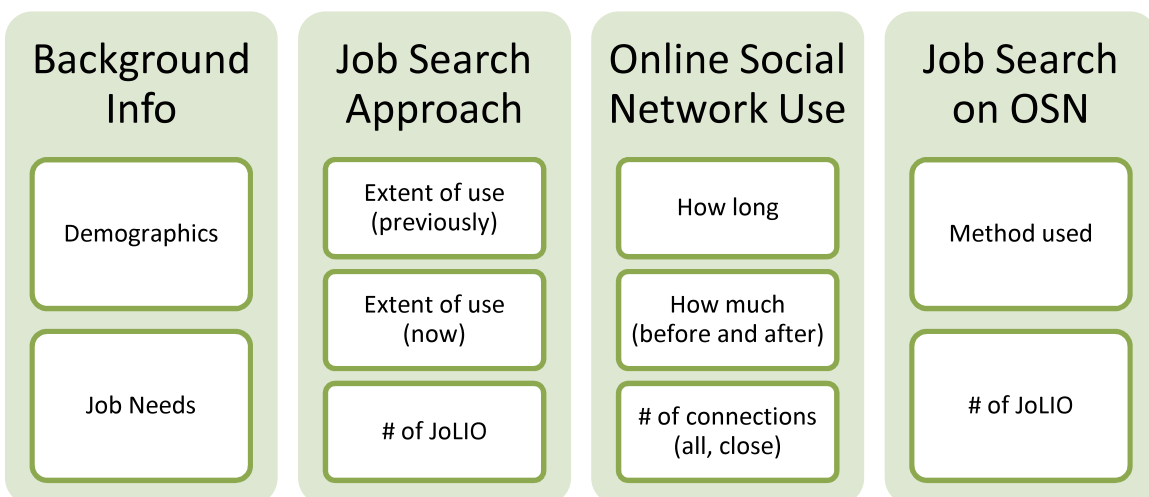
Online social networks have enabled the formation of larger social networks while increasing the transparency of information shared between individuals. This openness in sharing the information and larger potential for influence has changed the traditional approaches of evaluating the role of social capital. Some studies have tried to address the challenges of identifying the peer influence on online networks using randomized experiments (Aral, Muchnik, and Sundararajan 2009) or strategic dissection of archival data (Garg, Smith, and Telang 2011).

Online social networks allow users to maintain a large number of connections that are weak-ties; ties that exist between acquaintances found through work, focus groups, affiliations, etc. Individuals are able to find information about potential job opportunities more quickly because of reduced search costs and large number of weak-ties. But the role of this increased number of weak- or strong-ties on job outcomes is still novel to the field. Through this paper we try to take the first step at understanding the role of online social networks on job search by unemployed workforce using a survey data of recently laid-off individuals.

3 DATA

Traditionally labor economists have relied on National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users are searching for jobs and in some cases how do their social networks help them in job search (Holzer 1988). While these data have large observations, they do not contain many details that are needed to answers the question we outline in the introduction. For example, they do not have details on how many job leads, interviews and job offers a user has received. Most of these surveys also do not have any details on users' online social capital and search behavior.

To better understand the role of online social networks on job outcomes, we designed an IRB approved survey and administered it to individuals that lost their jobs at large (revenue in excess of $100 million) organizations across the United States during 2010. An outplacement consulting firm facilitated the survey by allowing us to administer the survey to people it was helping with job search. The survey contained questions about the individual's current employment status, their motivations for job search, their past and present job search strategies, their familiarity and use of online social networks, and their knowledge of using online social networks for job search. Thus the survey is much more detailed and required about 30 minutes of subject's time in answering all of the questions regarding their job search approach. The survey contains the following components:



To test if users would respond to the details asked in the survey and if the questions were clear, we created a pilot survey that was made available on the Internet and the link was shared with our peers and friends. The goal of the pilot was to gain any feedback to improve the questions to maintain the attention of job seekers during the entire time. We made some adjustments to the questions based on the feedback received and the actual data from this sample was ignored for the study.

The outplacement firm had access to 288 individuals whose emails were available to them. Of the 288 emails sent, 163 individuals opened the email and 109 individuals took our survey. 8 surveys were not fully complete, leaving us with 101 completed surveys. We paid $10 in Amazon.com gift cards to each individual who completed the survey; in addition we provided a job search strategy report created with help of professionals in the field. It should be clear that our survey was sent to mostly educated, white collar workers. So the sample is neither representative of general population nor is perfectly random. However, we also expect that educated and white collar workers are precisely the people likely to use online social networks. So our survey targets users who can provide useful insight into the phenomenon of interest. Within the selected population set, we believe there is enough interesting variation that allows us to examine the question of job search and online social network reliably. Summary demographics for these individuals are presented in Table 1. We also believe that the limitations of our survey are not any different than other well published survey papers.

Completed Surveys	109
Currently Unemployed	57
Married	53
Age (Average)	39 (8.97)
Total Work Experience (Average)	14.2 (6.3)
Approximate Salary (Average)	$78.7k (28.1)
Race = White	62
Race = Black	6
Race = Hispanic	7
Race = Asian	14

Table 1: Demographic summary for all survey takers

We asked users about five major search modes they used in job search (i) Internet (like monster.com), (ii) Online social networks (like LinkedIn), (iii) Offline close friends and family, (iv) Newspapers and print media, (v) job agencies and career fairs. Of 101 people, 89 individuals used internet as job search mode, 77 used online social networks for job search, 81 used their offline network of close friends and family, 56 used print media, and 43 used agencies (including career fairs, and placement services). Summary of the time spent on each of these modes and the time spent conditional on mode being used during last job search (sticky search) is given in Table 2. Table 2 shows how the job search behavior changed conditional on the search mode being selected during the current time period or the previous time period. Increase in the number of individuals using each job search mode suggests either the reduced search costs or the impact of unemployment. The only job search mode that stands out is online social networks, which gained a large increase in the use possibly because of the newness of the job search mode with large majority still adopting the platform.

Job Search Mode	Count	Search Intensity (hrs/week)	Search Intensity (condition of use in past) (hrs/week)
Agencies (AG)	43	4.79 (2.69)	2.76 (2.74)
Print Media (PM)	56	4.45 (3.13)	3.39 (3.46)
Internet Posts (IN)	89	14.39 (11.61)	13.27 (12.22)
Online Social Networks (SN)	77	8.79 (7.42)	6.85 (6.49)
Friends and Family (FF)	81	5.54 (4.13)	4.87 (4.37)

Table 2: Search intensity on each job search mode - conditional on using the search mode (mean values with std. dev.)

Interestingly we see that the share of time spent (conditional on the job search mode being used) on online social network for job search (31%) is slightly smaller than the share of time spent with close friends and family (33%). The share of search effort is largest for internet (49% on average) with print media (29%) and agencies (25%) as the lowest two. We explicitly ask users how many job leads, job interviews and job offers they found via each model. The summary of search effort distribution across job search mode, their search intensity on that mode, and job outcomes (number of leads, interviews, and offers) from each mode is presented in Table 3. The numbers are presented in terms of share (%).

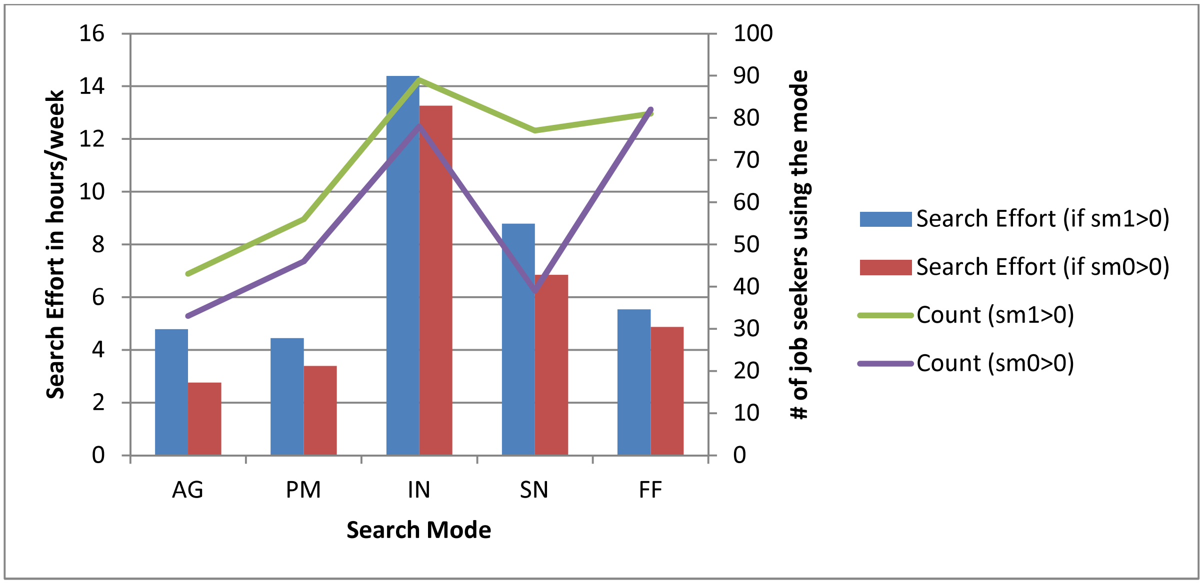


Figure 1: Job search mode selection and search effort allocation as a function of previous (sm0) or current (sm1) mode use

Job Search Mode	N	Effort	Leads	Interviews	Offers
Agencies (AG)	43	0.16 (0.1)	0.08 (0.12)	0.19 (0.2)	0.15 (0.2)
Print Media (PM)	56	0.16 (0.15)	0.17 (0.14)	0.17 (0.21)	0.18 (0.38)
Internet Posts (IN)	89	0.41 (0.2)	0.43 (0.25)	0.49 (0.29)	0.26 (0.39)
Online Social Networks (SN)	77	0.24 (0.12)	0.19 (0.2)	0.21 (0.23)	0.54 (0.39)
Friends and Family (FF)	81	0.19 (0.11)	0.23 (0.24)	0.32 (0.3)	0.49 (0.43)
N		96	96	83	43

Table 3: Search intensity & job outcome share on each job search mode

	Searched	Job Leads	Job Interviews	Job Offers
Internet	89	82	62	12
Online Social Networks	77	55	34	17
Close Friends & Family	81	70	49	18
Print Media	56	45	22	3
Agencies	43	19	12	3

Table 4: Job outcome count from various job search modes

Next we asked users to specify how many connections they have and how many they consider as weak and strong connections respectively. Distribution of total, strong, and weak connections on both Facebook and LinkedIn is presented in Figure 2. We observe that individuals have much larger share of strong-ties on Facebook yet a much larger share of weak-ties on LinkedIn. For individuals that did not use online social networks as a job search mode, we inquired about their distrust in that platform. All of the individuals (not using online social networks) selected privacy concern as the most important reason for not using online social networks (like Facebook) and lack of sufficient job leads for not using online professional networks (like LinkedIn).

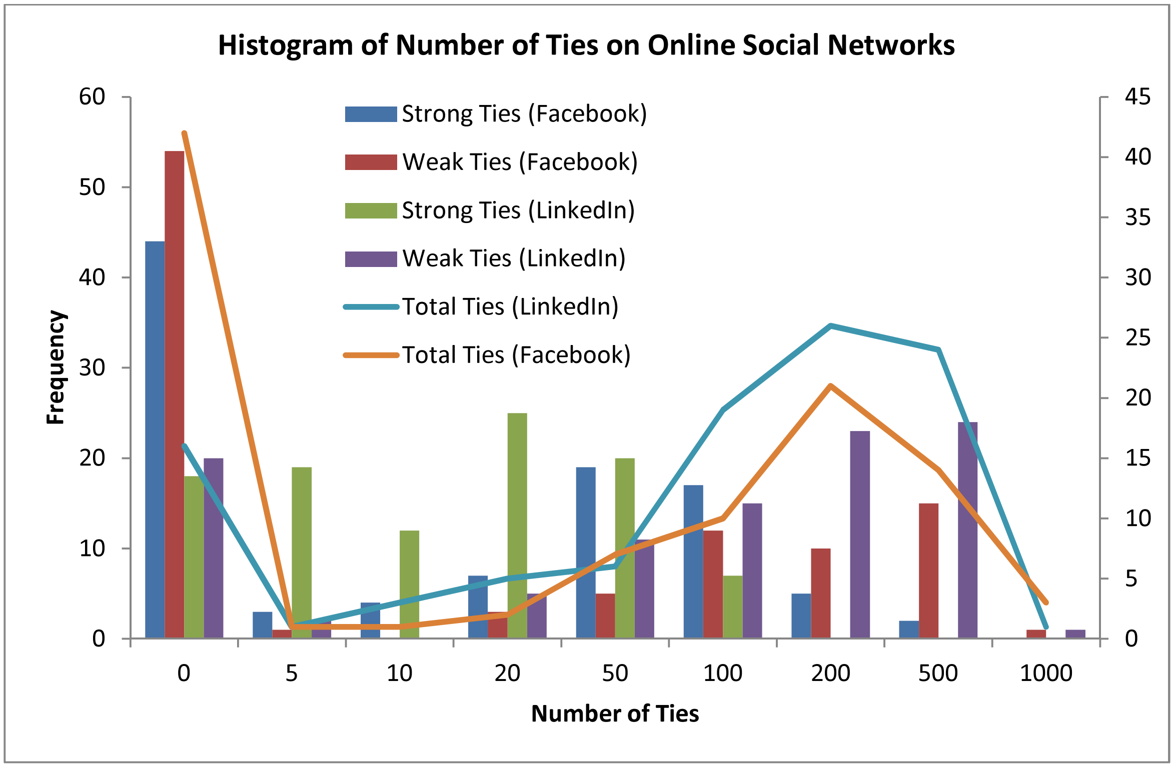


Figure 2: Distribution of number of online social ties on Facebook and LinkedIn

3.1 Job Search within Online Social Networks

Almost all of the job search modes could be further analyzed at a much more granular level to evaluate how individuals search for jobs on each of the modes. For example, an individual could use a newspaper's career section to find a new job or use the news section to find the companies that are growing and/or innovating in the area. Similarly individuals can search using various modes on online social networks. We identified four modes of job search on LinkedIn based on a separate set of responses from LinkedIn users. These four modes include 1) searching for job posts & ads on LinkedIn, 2) contacting close friends & family (strong-ties) on the online network for leads and/or references, 3) contacting other connections (weak-ties) on the online network for leads and/or references, and 4) finding and contacting recruiters for potential job opportunities.

	Search Effort (%)	Job Leads	Job Interviews	Job Offers
Job Posts	0.797 (0.405)	2.727 (4.61)	0.532 (1.06)	0.027 (0.164)
Strong-Ties	0.652 (0.48)	1.383 (2.285)	0.58 (0.883)	0.195 (0.401)
Weak-Ties	0.689 (0.467)	1.304 (3.202)	0.435 (0.72)	0.146 (0.358)
Recruiters & Headhunters	0.672 (0.473)	1.302 (2.25)	0.682 (1.308)	0.135 (0.419)
Other	1 (0)	0.875 (1.808)	0.081 (0.493)	0 (0)

Table 5: Search effort allocation and job outcomes from modes used on online social networks

Of the four modes, the second highest share of effort and highest share of job leads came from online job posts & ads, which is intuitive as individuals control the effort and get returns proportional to the effort. Most of the search modes on OSN received almost equal search intensity but job posts captured the highest share of leads, recruiters and headhunters received the largest share of interviews and strong-ties contributed to the largest share of job offers. Strong-ties did better and had a highest rate of converting job interviews to offers – this supports the argument of strength of strong-ties (Krackhardt 1992). Summary of the share of effort and job outcomes from these four modes is presented in Table 5.

4 THEORY

We are interested in exploring two main questions that we outline in the introduction. How do people allocate their times across different modes and how online connections affect those choices? And, do online connections affect job outcomes? A key goal is to understand how online social connections affect job outcomes. Unfortunately, job outcomes are also affected by how hard users are searching for jobs on a particular mode. Moreover, job search decision itself will be driven by how likely users think they will find a job. In short, the relationship between social connection, job outcomes and search effort is complex and requires a formal treatment to carry out a convincing empirical analysis.

Intuitively, the decision to allocate time across different search modes depends on users' expected benefits and cost calculation. In the following, we present a simple model that provides the basis for our empirical analysis. In the process, we will also outline some challenges in identification. We consider the following five job search channels: 1) agencies [AG] - like libraries, career fairs, etc, 2) print media [PM] - newspapers, magazines, etc), 3) internet job boards [IN] - like monster.com, hotjobs.com, etc, 4) online social networks [SN], and 5) close friends and family [FF].

4.1 JOB SEARCH ALLOCATION

We use and modify widely used income-leisure utility models (Burdett 1977; Mortensen 1986; Holzer 1988) to set up our empirical strategy. In particular, individuals make decisions on how much to search based on their expected benefits and costs.

These models assume that there is certain baseline utility from being unemployed. Searching increases the probability of being employed but it also has associated costs. So users are essentially trading off these two costs. In particular if users perceive social connections to be useful, we should see them searching more on those modes. More formally, we can specify the utility of an unemployed individual as:

$$U_{i,j,t}(w_R, s_j) = v_{i,j}(L_i - s_j, Y_i - c_j(s_j)) + \pi_{j,t}(s_j, X_i, E_i) * p_{j,t}(w_t \geq w_{R,t}) * E(U_{emp,(t+1)}) + (\pi_j(s_j, X_i, E_i)) * (1 - p(w_t \geq w_{R,t})) * U_{t+1} + (1 - \pi_j(s_j, X_i, E_i)) * U_{t+1} \quad \text{... (1)}$$

i indexes an individual, *j* indexes search model and *t* time. Here $v_{i,j}$ is the current period utility from leisure and outside income. Searching is costly, it reduces leisure time as well as incurs monetary cost c_j. , L_i is the leisure time for individual *i* and Yi is the non-wage income. The second term in the utility function is the expected utility of being employed if the probability of an offer is $\pi(s_j, X_i, E_i)$ and wage offer (w_t) is higher than reservation wage $(w_{R,t})$. Here X_i represents the user's characteristics (like education, experience, age, salary during last job, race, etc). E_i represents the embeddedness or social capital of user *i* on online social network (especially the number of connections on LinkedIn). The third term in (1) is simply the probability that users will remain unemployed because the wage offer is not higher than reservation wage and the fourth term indicates that the user may not get any offer despite searching and hence remain unemployed in the next period.

Most job search models also have reservation wage as a decision variable. So in a dynamic model, individuals are also choosing their reservation wage over time. Given the cross section nature of our data over a period, and that our focus is on empirical identification of how users connections play a role, we assume the reservation wages are exogenous. We will revisit this shortly. Assuming that the wage offer distribution is given as f(w), we can rewrite the above equation as:

$$U_{i,j,t}(s_j) - U_{i,j,t+1} = v_{i,j}\left(L_i - s_j, Y_i - c_j(s_j)\right) + \pi_{\mathrm{i,j,t}}(s_j, X_i, E_i) * \int_{\mathrm{w_R}}^{\infty}\left[\mathrm{E}\left(U_{emp,(t+1)}\right) - U_{i,j,t+1}(w_R, s_j)\right] * \mathrm{f}(w)\mathrm{d}w \quad \ldots (2)$$

The equation specifies expected change in utility over two time periods due to investing in search effort s. The first part is reduction in utility due to searching. The second part is increase in utility due to searching. Users invest in search intensity "s" to maximize this utility. So optimal search time s* is given by taking the derivative and equating it with zero.

However, for empirical tractability, we need to assume functional forms for both cost and job offer rate. We will rely on prior literature for these functions. *v* is assumed to be linear in its arguments (Holzer 1988). Given that these are unemployed users who have more available time to search, the cost of search on leisure can be minimal. Thus we can ignore the first argument in function *v*. The offer probability is a linear combination of the offer arrival rate (λ) and search effort allocated to a job search mode (Bloeman 2005). We will suppress subscript *t*:

$$\pi_{\mathrm{i,j}}\left(s_{ij}, X_i, E_{i,}\right) = \lambda_{\mathrm{i,j}}\left(X_i, \mathrm{E_j}\right) * \left(\tau_0 + \tau_1 \mathrm{s_{ij}}\right) \quad \ldots (3)$$

$$where\ \lambda_{\mathrm{i,j}}(X_i, E_i) = \exp\left(\varphi_{0j} + \varphi_1 X_i + \varphi_{2j} E_i\right)$$

Here λ is the offer arrival rate on a search mode during a given time period that is dependent on the user characteristics *X* and embeddedness *E* of a job seeker. We also include a dummy φ_{0j} to control for mode specific unobserved. *E* suggests that if a job seeker has higher social connections on a particular search mode, s/he is more likely to receive job offers. It is also clear from π that higher the efforts on search, more is the likelihood of receiving an offer. A constant τ_0 allows for the fact that even zero search effort could lead to some positive job outcomes.

Finally, we also assume a functional form for the search cost (Bloemen 2005) as:

$$\mathrm{c_j}(s_j) = \gamma_j * \exp\left(-\frac{\delta_j * X_i}{\gamma_j}\right) * \left[\exp\left(\frac{s_j}{\gamma_j}\right) - 1\right] \quad \text{... (4)}$$

As expected cost is increasing in search efforts and it is convex. Given that the benefit of search is linear, an interior solution is guaranteed. Taking first order of (2) will yield:

$$-v_2 \alpha_1 \exp\left(\frac{\mathrm{s_{i,j}}}{\gamma_\mathrm{j}}\right) + \tau_1 \lambda_{\mathrm{i,j}}(X_i, \mathrm{E_i}) * \mathrm{R_{i,j}} = 0$$

$$\text{where} \quad \mathrm{R_{i,j,t}} = \int_{\mathrm{w_R}}^{\infty} \left[\mathrm{E}\left(U_{emp,(t+1)}\right) - U_{i,j,t+1}(w_R, s_j)\right] * \mathrm{f}(w)\mathrm{d}w$$

$$\text{and} \quad \alpha_1 = \exp\left(-\frac{\delta_j * X_i}{\gamma_j}\right)$$

Since *v* is linear, v_2 (derivative of v wrt to its second argument) is simply a constant which we normalize to 1. Solving for optimal s and simplifying (3) leads to:

$$s_{i,j}^* = (\gamma_j * \log \tau_1) + (\varphi_{j,0} * \gamma_j) + (\delta_j + \gamma_j * \varphi_1) * X_i + \varphi_{j,2} * \gamma_j * E_i + \gamma_j * \log(\mathrm{R_{i,j}}) \quad (5)$$

Since we observe s_{ij}, the difference between observed and predicted s is simply the error component. Thus an estimable form would be

$$s_{i,j} = s_{i,j}^* + \varepsilon_{ij} \quad \text{... (6)}$$

While we have data to estimate this equation, there are many challenges.

First we do not directly observe R. Note that R is the expected benefit of employment given the distribution of wages distribution w. We follow the approach suggested in prior literature (Mortensen 1986; Bloemen 2005) that assumes the difference in the utility from employment and the utility from the unemployed search to be equal to the difference in employed wage and reservation wage. This further simplifies the equation since we know the past wage of the user; we assume that reservation wage is proportional to the past wage[3]. If wage offer distribution is normal for a job search mode then:

$$\mathrm{R}_{\mathrm{i,j,t}} = \int_{\mathrm{w}_{\mathrm{last}}}^{\infty} [\mathrm{w} - w_{last}] * \mathrm{N}(\mathrm{w}, \overline{w}, \sigma^2)\mathrm{d}w$$

Since we know how much each job seeker received in the last job, we can create a distribution for each of the job search modes. Summary of the mean and standard deviation of wages is given in Table 6.

	N	Mean ($1000s)	Std. Dev.
Internet	24	74	30.06
Online Social Networks	14	88	22.82
Close Friends & Family	39	83	26.55
Print Media	10	52	19.89
Agencies	10	70	29.81

Table 6: Mean and std dev of wage on various job search modes

4.2 EFFECT OF EMBEDDEDNESS ON JOB OUTCOME

Once an unemployed job-seeker allocates time to each job search mode, the next step is to estimate the role of social embeddedness on the job outcomes. Our job offer model is straight-forward.

$$\pi_{\mathrm{i,j,t}}(s_j, X_i, E_i) = (\tau_{0\mathrm{j}} + \tau_{1\mathrm{j}}\mathrm{s}_\mathrm{j}) * \exp(\varphi_{0j} + \varphi_{1j}X_i + \varphi_{2j}E_i)$$

[3] One would expect that reservation wage will change with time. But we do not observe the users repeatedly, and hence use average of past wage and new wage (for those who found jobs) as a proxy for reservation wage.

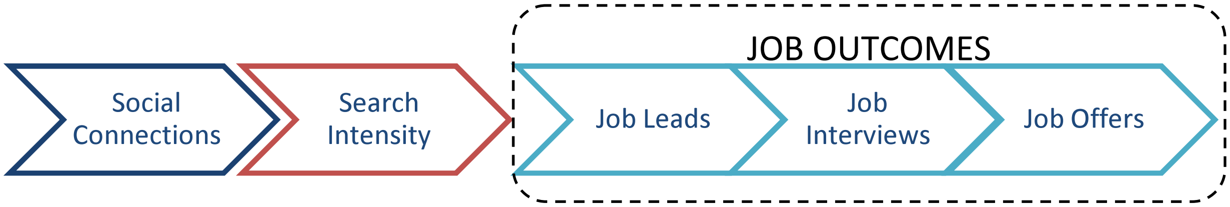
Most models who estimate effect of social capital on job outcomes do not capture any details on search intensity "s" which is problematic as we show.

Embeddedness can affect job outcomes in two ways. First, as our model in (4) shows, more connections may lead to more search effort by users. Second, more connections would lead to more job outcomes independent of search effort. Formally, the effect of embeddedness on job outcome could then be written using the chain rule as follows:

$$\frac{\mathrm{d}\pi_{\mathrm{i,j}}}{\mathrm{dE_i}} = \frac{\partial\pi_{\mathrm{i,j}}}{\partial \mathrm{E_i}} + \frac{\partial\pi_{\mathrm{i,j}}}{\partial s_j} * \frac{ds_j}{d\mathrm{E_i}}$$

Many empirical papers do not have details on search efforts. That is, the second term in the equation above is not estimable. It is clear that without measuring "s", effect of embeddedness on job outcomes will be seriously under (or over) estimated. In our paper, by directly observing s and E, and writing down the structure of search effort, we can estimate how social capital effects search outcomes cleanly by estimating all components of the above equation.

An even more interesting aspect of our data is the granularity in job outcomes. Most papers measure only job offer as an outcome. However, the actual job offer process is more complex. Usually job search efforts generate relevant job leads. Job leads covert to interviews and finally offers. The effect of social capital would be different on these outcomes. For example, we would expect weak ties to have a strong effect on job leads. Weak ties may be able to provide a user to potentially relevant job lead. The cost of diffusing information across weak links is low. However, weak ties may not influence interviews or offer probabilities. Strong ties can potentially play a bigger role. Interviews and offers depend on people willing to make phone calls, or write recommendation letter on behalf of a user, or press for a user's prospect. This is costly and only strong ties may be willing to make these investments.



In short, if we get access to more granular outcomes we can get better insights into how social connections affect job outcomes. In this paper, we focus on three outcomes: job leads, job interviews and job offers. It is clear that these are linked sequentially. We build on the productivity model (Blau and Robins 1990) such that there is a sequential process of search leading to job leads to job interviews and eventually to job offers. Thus, we can write the job offer as a function of outcomes (interviews, which is a function of search). Or,

$$JO_{\mathrm{j}}(s_j,\, X_i,\, E_i) = \mathrm{f}\left(JI_j\left(JL_j\left(s_j(\,X_i,\, E_i)\right)\right)\right)$$

Here JO is the number of job offers received from the search mode j, when a job seeker received JI interviews and JL job leads from search effort s. This brings us back to the job outcome function with the modification of dependent variable being the job outcome in the sequential process.

$$\mathrm{JO_{i,j}}(\mathrm{JI_{i,j}},\, X_i,\, E_i) = \left(\tau^1_{0,\mathrm{j}} + \tau^1_{1,\mathrm{j}}\, \mathrm{JI_{i,j}}\right) * \exp\left(\varphi^1_{0,\mathrm{j}} + \varphi^1_1 X_i + \varphi^1_{2,\mathrm{j}} E_i\right) + \varepsilon^1_{\mathrm{j}}$$

$$\mathrm{JI_{i,j}}(\mathrm{JL_{i,j}},\, X_i,\, E_i) = \left(\tau^2_{0,\mathrm{j}} + \tau^2_{1,\mathrm{j}}\, \mathrm{JL_{i,j}}\right) * \exp\left(\varphi^2_{0,\mathrm{j}} + \varphi^2_1 X_i + \varphi^2_{2,\mathrm{j}} E_i\right) + \varepsilon^2_{\mathrm{j}}$$

$$\mathrm{JL_{i,j}}(\mathrm{s_{i,j}},\, X_i,\, E_i) = \left(\tau^3_{0,\mathrm{j}} + \tau^3_{1,\mathrm{j}}\, \mathrm{s_{i,j}}\right) * \exp\left(\varphi^3_{0,\mathrm{j}} + \varphi^3_1 X_i + \varphi^3_{2,\mathrm{j}} E_i\right) + \varepsilon^3_{\mathrm{j}}$$

Using the chain rule the effect of embeddedness on job outcomes could be readily calculated as follows:

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{dJI_j}{dE_{i,j}}$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}}$$

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}}$$

In addition to estimating the effect of embeddedness on various job outcome classifications, the above model also allows us to estimate the effectiveness of each job search mode in converting search effort to job leads, job leads to interviews, or job interviews to offers. Next we discuss the role of search intensity allocation on job outcome from each job search mode.

5 EMPIRICAL ANALYSIS & RESULTS

5.1 Search Effort Allocation

As discussed previously and in prior research (Mouw 2003) it is important to understand the role of social capital on the search effort to clearly identify any issues relating to endogeneity or homophily (McPherson, Smith-Lovin, and Cook 2001). Individuals with larger social capital could gain benefit from their network because they are connected to a few influential and highly social individuals and there might be no significant value provided by the entire network. Thus it was suggested (Mouw 2003) that a clean identification should include the effect of social capital on the search effort because a large social capital would require more effort and thus could eventually convert that effort into positive job outcomes. Thus, as a first step, we test if size of social capital indeed plays a role in the search effort allocated to online social network by the unemployed workforce.

Our regression equation is

$$s_{i,j} = \left(\gamma_j * \log \tau_1\right) + \left(\varphi_{j,0} * \gamma_j\right) + \left(\delta_j + \gamma_j * \varphi_{j,1}\right) * X_i + \varphi_{j,2} * \gamma_j * E_i + \gamma_j * \log\left(\mathrm{R_{i,j}}\right) + \varepsilon_{ij}$$

The first two terms are simply a constant, while the other terms are readily identified. As we will show, we can recover structural parameters for cost (γ_j, δ_j) readily. We simplify the equation above as

$$s_{i,j} = \alpha_0 + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(\mathrm{R}_{\mathrm{i,j}}) + \varepsilon_{ij}$$

Even though we do not observe users choices repeatedly, we do observe the same user over five modes. Thus we have a panel data set which allows us to control for user specific and search mode specific unobserved. So we can rewrite this as

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(\mathrm{R}_{\mathrm{i,j}}) + \varepsilon_{ij}$$

ω_i is user specific dummy and θ_j is mode specific dummy. If we include user specific fixed effects, we cannot estimate α_1 and α_2 directly. So we will control for user heterogeneity in the form of user random effects. Notice that by controlling for user and mode specific heterogeneity, we control for significant unobserved variations across modes and users. We will split E_i into strong and weak ties separately to explore how these ties affect search time.

The key variable of interest is the estimate on social embeddedness, α_2. A positive estimate suggests that users with higher online connections search more. However, there are many potential issues

(i) *Users are searching more because they expect more job offers which is unobserved.* Notice our optimal search model automatically incorporates the benefit function. From the benefit function it is clear that search efforts will be higher if $\varphi_{j,2}$ (effect of social connections on job outcomes) is positive and large. Thus in our model, a positive estimate on E is precisely because users expect E to influence job outcomes. We also use expected wages R as a way to control for expected wage distribution on a search mode.

One may still worry that some unobserved mode specific characteristics would not only drive search time but will also drive social capital. So a mode may be more productive for reasons unknown. We control for these by using mode specific dummies.

(ii) Another worry is reverse causality. If users spend more time on LinkedIn looking for jobs, they are more likely to make more social connections. In our data, we ask users explicitly how many connections they had before they lost their jobs. Moreover, we also include unemployment duration as a possible control. Though notice that we are testing the effect on online connections on search behavior on other modes as well.

(iii) One may still worry that some unobserved may be correlated with embeddedness. For example, more social users may search more on online social networks and also have more connections. First we use user specific random effects to control for unobserved. We also use Facebook connections as a control. So if users are more social, they are also more likely to have larger connections on Facebook.

After adding all controls, we have an estimable form for job search efforts as:

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(\mathrm{R_{i,j}}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \qquad (7)$$

We include additional control in the form of E_i^F which is users' Facebook connections. Dur_i is the users' unemployment duration.

We run two separate specifications. First is specification (7) where we split the online connections (E_i) into strong and weak connections and estimates their effect on search effort. Notice that (7) estimates the effect of E on search effort across all modes. Thus we examine if higher number of strong (and weak) ties affect search effort on other modes. However, as we outlined earlier, the effect may be dependent on the search model itself. In the second specification, we treat online social networks as one potential search mode and the remaining four modes as "other modes". We then interact E_i with these two modes. The goal is to estimate the marginal effect of an online tie (weak and strong) on search effort when the search mode is LinkedIn vs. other modes. Thus in this specification we examine if strong (and weak) ties affect search time on online social network search model vs. the other modes.

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * E_i * D_s + \alpha_2 * E_i * D_o + \alpha_3 * X_i + \alpha_4 * \log(\mathrm{R_{i,j}}) + \alpha_5 * E_i^F + \alpha_6 * Dur_i + \varepsilon_{ij} \qquad (7a)$$

Ds is dummy for online social network search mode while *Do* is a dummy for any other mode. The estimates of these three separate regressions are given in the two columns of Table 7 below. The left out dummy (in θ_j) is the search mode "agencies".

In the first column, notice that the coefficients for all dummies are significant. This suggests people spend more time on online social network, Internet, print media and with friends and family for job search relative to agencies. The number of strong ties (but not the weak ties) affects job search intensity on all modes. People with more strong ties search more on all modes. In terms of economic significance, an estimate of 0.97 indicates that a 100% increase in number of strong ties increases the search effort by about 1 hour per week. This follows from the traditional argument about multiplexed ties (Verbrugge 1979), which suggests that some social connections could have overlapping social relationships. We believe these strong-ties exhibit multiplexed relationships that spans across various modes of communication (like online or offline) and thus affect the search behavior across various job search modes. Surprisingly, we find no effect of online weak ties on aggregate search effort. The estimate is economically and statistically insignificant. No other estimates are significant except race where the left out category is "other races". That demographic variables are not significant is expected given we control for user specific random effects and mode specific dummies.

Search Effort (hours/week)	**Coeff (Std Dev)**	**Coeff (Std Dev)**
Dummy (Online Social Networks)	6.685 (1.805)***	2.638 (1.985)
Dummy (Offline Friends & Family)	2.087 (1.011)**	2.121 (1.018)**
Dummy (Internet)	10.919 (2.422)***	10.939 (2.428)***
Dummy (Print Media)	3.662 (1.892)*	3.535 (1.906)*
Log (LinkedIn Strong-Ties)	0.972 (0.441)**	
Log (LinkedIn Weak-Ties)	0.092 (0.231)	
SN * Log (LinkedIn Strong-Ties)		0.921 (0.651)
SN * Log (LinkedIn Weak-Ties)		0.815 (0.362)**
OT * Log (LinkedIn Strong-Ties)		0.986 (0.453)**
OT * Log (LinkedIn Weak-Ties)		-0.089 (0.247)
Log (Total Facebook Ties)	0.075 (0.174)	0.075 (0.174)
Log (Unemployment Spell)	0.596 (0.448)	0.596 (0.449)
Log (Salary)	4.582 (2.657)*	4.56 (2.661)*
Experience	0.106 (0.091)	0.106 (0.091)
Sex (male = 1)	-1.645 (0.992)*	-1.645 (0.995)*

Married (yes = 1)	-0.266 (0.912)	-0.266 (0.913)
Education (Diploma)	-1.76 (1.881)	-1.761 (1.886)
Education (Bachelors)	-2.285 (1.709)	-2.285 (1.713)
Education (Masters)	-2.186 (1.851)	-2.186 (1.856)
Education (Doctorate)	-0.955 (2.538)	-0.952 (2.544)
Race (White)	7.761 (2.41)***	7.765 (2.415)***
Race (Black)	8.347 (2.845)***	8.351 (2.85)***
Race (Hispanic)	7.823 (2.618)***	7.827 (2.623)***
Race (Asian)	6.78 (2.528)***	6.783 (2.533)***
Employment Value (Online Social Networks)	0.36 (1.062)	0.56 (1.049)
Employment Value (Offline Friends & Family)	1.391 (0.903)	1.33 (0.913)
Employment Value (Internet)	1.45 (1.449)	1.389 (1.451)
Employment Value (Print Media)	0.605 (0.374)	0.58 (0.378)
Employment Value (Agencies & Career Fairs)	1.499 (0.865)*	1.442 (0.873)*
_cons	-31.971 (11.969)***	-31.08 (12.028)**
R2	0.326	0.333

N = 450, ordinary least square regression estimates
User (90 groups) random effect
Standard deviation in parenthesis
Significance: *(p<0.1), **(p<0.05), ***(p<0.01)
Omitted dummies: Race(Other), Education(Other), Search Mode (Agencies)

Table 7: Time spent on job search using various job search modes

In the first column we tested the aggregate effect of online ties on job search, now we examine the effect of these ties on search behavior on online social network relative to other modes. To accomplish this we created two dummies and interacted online ties with those dummies. The results are presented in column 3 of Table 7. Given that we are interacting mode dummies with online ties, the estimates on dummies are not different. In particular, the estimate on online social network is much smaller. However, its interpretation is also different. An estimate of 2.63 simply suggests that users spend 2.63 hours more on social network relative to agency if the number of connections is zero. As their connections increase, so does their time.

Now, the estimate on weak ties interacted with social network is positive and significant. This suggests users with more weak online ties are more likely to search on online social network. A 100% increase in weak ties increases the time by about 0.8 hours per week. However, the estimate on strong ties is not significant for online network. Users with more strong online ties do not search more on online networks. It is the weak ties that stimulate higher search intensity.

However, interaction of strong ties with other nodes is still significant. More number of online strong ties stimulates more search on other modes but more number of weak ties stimulate more search on social networks. An implication of this result is that strong ties, in general, suggest a social capital that is not specific to a mode and may suggest the multiplexed nature of those relationships. However, online weak ties probably cannot be readily leveraged on other modes. Since SNS allow users to connect with a large number of weak-ties at a small or no cost, these ties could be perceived valuable only on the platform of connection. Taking an example, if John Doe is connected with a close buddy Sam Smith on LinkedIn, he can utilize his help with job search irrespective of a job search mode being discussed. On the other hand if John worked with Sarah Jones during one of his internship during college and got connected with her on LinkedIn, he probably won't call her to ask for job leads and most likely will send her a message updating her about his employment status first. Thus strong-ties that add to social capital define the job search behavior of an unemployed individual in general but the weak-ties on a SNS contribute to the changed behavior on that specific social networking site.

5.2 Job Outcomes

5.2.1 Sequential Model (Search Intensity Affecting Job Leads)

As discussed earlier job search delivers outcomes that are sequential in nature; search effort will typically allow users to apply for relevant job opportunities, which will allow employers to call the job seeker for interviews and eventually make an offer. Since we collected information from job seekers about each of the job outcomes we are able to understand the role of search on job leads and subsequently on other outcomes. Thus we could estimate if one search mode is more effective in converting search to leads, leads to interviews or interviews to offers. We believe that this information is useful for job seekers because of the portability of information enabling them to maximize the returns by using a blend of various job search modes.

Here we consider the following three non-linear models:

$$\mathrm{JO}_{\mathrm{i,j}}\left(\mathrm{JI}_{\mathrm{i,j}},\, X_i,\, E_i\right) = \left(\tau^1_{0,\mathrm{j}} + \tau^1_{1,\mathrm{j}}\, \mathrm{JI}_{\mathrm{i,j}}\right) * \exp\left(\varphi^1_{0,\mathrm{j}} + \varphi^1_1 X_i + \varphi^1_{2,\mathrm{j}} E_i\right) + \varepsilon^1_{\mathrm{j}}$$

$$\mathrm{JI}_{\mathrm{i,j}}\left(\mathrm{JL}_{\mathrm{i,j}},\, X_i,\, E_i\right) = \left(\tau^2_{0,\mathrm{j}} + \tau^2_{1,\mathrm{j}}\, \mathrm{JL}_{\mathrm{i,j}}\right) * \exp\left(\varphi^2_{0,\mathrm{j}} + \varphi^2_1 X_i + \varphi^2_{2,\mathrm{j}} E_i\right) + \varepsilon^2_{\mathrm{j}}$$

$$\mathrm{JL}_{\mathrm{i,j}}\left(\mathrm{s}_{\mathrm{i,j}},\, X_i,\, E_i\right) = \left(\tau^3_{0,\mathrm{j}} + \tau^3_{1,\mathrm{j}}\, \mathrm{s}_{\mathrm{i,j}}\right) * \exp\left(\varphi^3_{0,\mathrm{j}} + \varphi^3_1 X_i + \varphi^3_{2,\mathrm{j}} E_i\right) + \varepsilon^3_{\mathrm{j}}$$

As before, we control for mode specific unobserved effect by using a mode specific dummy. We allow the errors to be correlated for the same user using different modes. This controls for user specific unobserved.[4] As before, we estimate two models. In the first one we estimate the effect of online ties E (strong and weak) on job leads, interviews, and offers from all search modes. In the second, we estimate the marginal effects of ties on leads, interviews, and offers from online social network search mode vs. all other models.

Since we are estimating nonlinear regression, we report the marginal effects as opposed to the absolute parameter estimates. They are presented in Table 8 below.

First we look at the job leads model. First notice that more search increases job leads significantly. Every additional hour of searching is associated with 0.33 additional leads. Notice that the effect of ties on job outcomes is not straightforward. More ties affects search which in turn affects leads. However ties have a direct effect on job outcomes. From the results in column (1), the effect of strong ties is to decrease the number of leads across all modes but the effect of weak ties is to increase the job leads. The estimates are large and significant. Doubling the number of weak ties leads to about 0.7 more leads. The effect of strong ties is surprising. Higher number of strong online ties seems to reduce the number of leads. It may be that users with more strong ties alone are not very useful in generating leads possibly because strong-ties tend to provide little or no new information to a job seeker. By definition most job leads are new piece of information that serves as potential job opportunities matching a user's skills for which a job seeker submits a customized job application. A large number of weak ties are thus needed for new job lead generation.

[4] We cannot add a random effect readily given that we are estimating non-linear regressions.

	Job Leads		Job Interviews		Job Offers	
	effect of ties on all modes	Effect of ties on OSN vs other modes	effect of ties on all modes	Effect of ties on OSN vs other modes	effect of ties on all modes	Effect of ties on OSN vs other modes
	(1)	(2)	(3)	(4)	(5)	(6)
Search Intensity	0.336 (0.064)***	0.332 (0.066)***				
Job Leads			0.106 (0.029)***	0.105(0.029)***		
Job Interviews					0.107 (0.024)***	0.081 (0.019)***
Dummy (OSN)	0.469 (1.294)	-3.405 (1.648)**	-0.547 (0.287)*	1.272 (1.099)	0.259 (0.223)	0.148 (0.075)**
Dummy (FF)	1.222 (1.427)	1.101 (1.411)	-0.346 (0.341)	-0.354 (0.344)	0.094 (0.185)	0.022 (0.112)
Dummy (Internet)	2.156 (1.471)	1.984 (1.475)	0.257 (0.381)	0.251 (0.383)	-0.006 (0.132)	-0.011 (0.084)
Dummy (Print Media)	0.821 (1.388)	0.62 (1.362)	-0.508 (0.272)*	-0.51 (0.27)*	-0.046 (0.158)	-0.074 (0.099)
Log (Strong-Ties)	-1.054 (0.405)***		0.367 (0.145)**		0.091 (0.03)***	
Log (Weak-Ties)	0.741 (0.251)***		-0.116 (0.095)		0.002 (0.016)	
SN * Log (Strong-Ties)		-0.303 (0.596)		0.06 (0.025)*		0.106 (0.04)***
SN * Log (Weak-Ties)		1.234 (0.453)***		-0.243 (0.11)**		-0.044 (0.02)**
OT * Log (Strong-Ties)		-1.224 (0.4)***		0.402 (0.15)***		0.108 (0.02)***
OT * Log (Weak-Ties)		0.767 (0.246)***		-0.116 (0.101)		0 (0.014)
Log (Facebook Ties)	0.125 (0.16)	0.126 (0.155)	0.099 (0.069)	0.102 (0.068)	0.028 (0.011)**	0.019 (0.009)**
Log (Unemployment Spell)	0.103 (0.323)	0.078 (0.317)	0.024 (0.134)	0.015 (0.128)	0.014 (0.033)	-0.022 (0.018)
Log (Salary)	0.487 (1.041)	0.272 (1.081)	0.533 (0.402)	0.517 (0.402)	-0.195 (0.073)***	-0.156 (0.046)***
Experience	0.034 (0.059)	0.033 (0.059)	-0.024 (0.024)	-0.025 (0.025)	-0.03 (0.005)***	-0.026 (0.005)***
Married (yes = 1)	0.747 (0.773)	1.001 (0.742)	-0.333 (0.341)	-0.321 (0.341)	0.385 (0.111)***	0.302 (0.089)***
Sex (male = 1)	-1.835 (0.578)***	-1.72 (0.554)***	0.112 (0.231)	0.1 (0.234)	-0.055 (0.055)	-0.079 (0.044)*
Education (Diploma)	-3.213 (0.78)***	-3.258 (0.753)***	-0.349 (0.469)	-0.412 (0.445)	-0.147 (0.06)**	-0.131 (0.038)***
Education (Bachelors)	-2.377 (0.979)**	-2.464 (0.924)***	-0.109 (0.369)	-0.095 (0.383)	-0.163 (0.071)**	-0.155 (0.053)***
Education (Masters)	-2.258 (0.903)**	-2.296 (0.87)***	-0.423 (0.4)	-0.392 (0.414)	-0.044 (0.053)	-0.036 (0.039)
Education (Doctorate)	-1.416 (1.505)	-1.546 (1.338)	-1.241 (0.178)***	-1.228(0.181)***	-0.077 (0.102)	-0.09 (0.051)*
Race (White)	-1.485 (2.485)	-1.819 (2.377)	-8.964 (9.19)	-8.899 (9.213)	0.022 (0.08)	0.104 (0.052)**
Race (Black)	-2.042 (1.594)	-2.195 (1.393)	-1.526 (0.281)***	-1.524 (0.277)***	0 (0)	0 (0)
Race (Hispanic)	-0.059 (2.156)	-0.521 (1.891)	-1.828 (0.356)***	-1.825 (0.355)***	0 (0)	0 (0)
Race (Asian)	0.003 (2.277)	-0.291 (2.04)	-1.866 (0.6)***	-1.868 (0.598)***	-0.064 (0.078)	0.03 (0.062)
R2	0.704	0.711	0.656	0.652	0.662	0.685
N	319	319	252	252	170	170
Clusters	89	89	88	88	76	76
Conditional on	Search		Job Leads		Job Interviews	

Non-linear least square regression marginal effects
Standard deviation in parenthesis
Significance: *(p<0.1), **(p<0.05), ***(p<0.01)
Omitted dummies: Race(Other), Education(Other), Search Mode (Agencies)

Table 8: Job outcomes (leads, interviews, and offers) received as dependent variable for non-linear estimation

In column (2), we examine the effect of ties on outcomes from OSN vs the other modes. Now, the strong ties have no effect on job leads from social networks. However, weak ties are highly significant and quite large. Doubling the weak ties leads to 1.2 additional job leads. While the effect of weak ties on other modes is also positive, the estimate is smaller than for OSN (both Wald test and t-test confirm this). The effect of strong ties is still negative and significant for other modes.

In column (3), we estimate the probability of interviews conditional on job leads. Notice that the effect of OSN strong ties is now highly significant but that of weak ties is not. This suggests strong ties do a much better job of converting leads into interviews. When we interact ties with search modes, the effects persist (see column 4). Now the weak ties are negative and significant for OSN. More weak ties are not necessarily useful in converting leads into interviews. It may be that for leads to convert into interviews, ties have to make phone calls or write recommendation letters. These are costly activities and only strong ties may be willing to do this and not the weak ties. So while weak ties may help you get a lead, they do not necessarily help in converting these leads into interviews.

Coming to job offers (column 5 and 6), we see the results consistent with those seen from the job interview regression – strong-ties play a significant positive role in job offers and weak-ties suggest a negative or no effect on the job offers. Doubling of strong ties leads to 0.1 more offer. The effect is persistent across modes.

An interesting and counter-intuitive finding here is the negative marginal effect of weak-ties on job interviews and job offers. We believe this supports Krackhardt's paraphrased[5] statement "a friend of the world is no friend of mine" and more formally as principle of reflected exclusivity (Krackhardt 1998), suggesting that a large number of weak-ties may reduce the strength of strong-ties, which in turn suggests a negative effect of weak-ties on the job interviews and offers received. Although we see these negative coefficients to be marginal effects of social connections on job outcome the true impact still needs to be evaluated and follows.

[5] Jean-Baptiste Poquelin (Moliere) The Misanthrope (1966) Act I, Scene I "L'ami du genre humain n'est point du tout mon fait" ("friend of the whole human race is not to my liking")

5.2.2 Role of Social Connections on Job Outcomes

However, the effect of ties on job outcome is a complex. As we explained earlier, more ties affect search intensity as well. Our estimates from Table 7 confirm that users with more ties are also more likely to search. To estimate the effect of social capital on job outcomes, we use the equation discussed in section 4.2:

Role of Strong-Ties on Job Outcomes (j= Online Social Network - LinkedIn)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = -0.303 + 0.332 * 0.921 \approx 0.0028$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = 0.060 + 0.105 * 0.0028 \approx 0.0603$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = 0.106 + 0.087 * 0.0603 \approx 0.1112$$

Role of Weak-Ties on Job Outcomes (j= Online Social Network - LinkedIn)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = 1.234 + 0.332 * 0.815 \approx 1.5046$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = -0.243 + 0.105 * 1.5046 \approx -0.0850$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = -0.044 + 0.087 * (-0.0850) \approx -0.0514$$

Thus for every 100% increase in number of weak-ties on LinkedIn, a job seeker can gain additional 1.5 job leads. But this 100% increase in weak-ties will decrease the number of job interviews by 0.085 and will decrease the number of offers by 0.051. Similarly, we can compute the net effect of strong connections on the job outcomes. For 100% increase in strong-ties on LinkedIn, we expect to see an increase in job leads by 0.003, increase in job interviews by 0.06, and an increase in job offers by 0.11.

In summary, the effect of change in strong- and weak- ties on job outcomes from online social network could be viewed as:

$$\Delta JL_{i,j} = 1.5 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.003 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}}$$

$$\Delta JI_{i,j} = -0.085 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.06 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}}$$

$$\Delta JO_{i,j} = -0.041 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.09 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}}$$

These three equations could be used to optimize the number of connections on online social networks to maximize the job outcomes. Although it may appear that strong-ties are most useful a job seeker needs to search more to get leads and more leads will convert to more interviews, which will give more offers. Thus one needs to find an optimal allocation of ties on online social networks like LinkedIn.

A major limitation here is that the marginal effect of strong-ties on search effort and on job leads is not statistically significant at 10% level (though they are significant at 20% level), thus this approach to estimate the effect of social connections on job outcomes should only be seen as a framework for future work. To better understand the net effect of search allocation and social capital on job outcome we will need to understand the confidence interval around each coefficient, which we leave for future extension of this work.

5.2.3 Estimating Structural Parameters

Since we use a structured approach as understanding the job search behavior and job outcome from various modes, we are able to recover the structural parameters in both the cost and benefit functions. Estimates for the parameters in the cost function are given in the table below:

$$\mathrm{c_j}(s_j) = \gamma_j * \exp\left(-\frac{\delta_j * X_i}{\gamma_j}\right) * \left[\exp\left(\frac{s_j}{\gamma_j}\right) - 1\right]$$

Structural Parameter	OSN	FF	IN	PM	AG
γ_j	0.559	1.5	1.169	0.595	1.451
δ_j (FB_Connections)	0.081	0.055	0.064	0.080	0.056
δ_j (Log(Unemployment_Spell))	0.774	0.762	0.766	0.773	0.763
δ_j (Log(Salary))	6.249	6.213	6.226	6.248	6.215
δ_j (Experience)	0.049	0.041	0.044	0.048	0.041
δ_j (Married)	-0.748	-0.322	-0.472	-0.732	-0.344
δ_j (Sex_Male)	-0.706	-0.937	-0.856	-0.715	-0.925

From the cost function, we see that online social networks have the smallest coefficient for the search costs suggesting the value of the platform. We believe that it is intuitive that online social networks have lowest value because they tend to combine the strengths of online platform for almost costless communication with social ties that individuals are comfortable communicating with. On the other hand, we believe that the cost of search is highest for offline friends and family because it takes significant effort and time to update those connections about job loss and seek help to find a new job. Internet seems to be a platform with surprising results for cost coefficient and we believe this is the case of information overload. Unemployed job seekers may find numerous opportunities on the internet and may find it hard to pick the ones worth the time it takes for submitting a job application.

The coefficients for print media and agencies are somewhat intuitive as magazines and newspapers are available ubiquitously and provide only limited information that could be processed by a job seeker in a give time frame. The cost for agencies is high because of interpersonal communication need similar to offline friends and family.

The estimation of structural parameters for benefit function is in work and will be available in future revisions of this paper.

6 CONCLUSION & DISCUSSION

This study, like most survey based studies, faces the limitation of not representing the entire population accurately. The survey responses received from the unemployed job seekers represent more educated and higher income individuals. Still, this is the first study - to the best of our knowledge – that investigates the role of online social networks in labor market. We have found that the continuously expanding social capital plays an important role in the job search. But since the effect of weak- and strong- ties is different in the job market, the results presented here could be used to strategically build a social capital to maximize the job offer probability.

In this study, we have developed an empirical structural job search model to describe the behavior of job seekers and to find the optimal search effort allocation. This approach was useful to address the rising concern about homophily when estimating the role of social capital in the labor market. Unfortunately this study does not conduct a controlled random experiment that would minimize the effect of homophily, but it does a reasonable job of suggesting that online social capital has a positive effect on time spent by job seekers on online social networks. This is intuitive because larger social capital will imply more opportunities to find new information though the network. Here we found that larger social capital will increase the search intensity allocated to both offline or online social job search modes and will cannibalize the time spent on Internet for job search.

This study also echoes the argument (Kuhn and Skuterud 2004) suggesting that the internet enabled or low-cost job search platforms could reduce the perceived value of a job seeker. This could also be assumed to exist because internet-enabled platform results in many job applications for every job posting whereas the print media requires more effort for each application and thus results in fewer applications leading to higher number of job interviews. This difference in outcome from job search modes has been used to suggest the value of information portability by many career transition experts. These industry experts suggest finding job leads from various job search modes and applying for positions like job seekers did a decade ago – mailing in a hardcopy cover letter with resume. This could then improve the chances receiving interview calls for every application.

Furthermore, we used the productivity model for understanding the role of social capital on job offers and intermediate job outcomes – this is important because it allows us to estimate the effect of effort on a more direct outcome. This allows a job seeker to maximize the offer probability if information from one search mode could be ported to another mode. For example, a job seeker could find job leads through internet and then tap into her social capital to convert those leads to interviews and offers. This porting of information might cause confounding effect in a research study, especially in the case of close friends & family and friends & family on online social networks. We found positive effect of weak-ties on job leads (new information) and positive effect of strong-ties on the job offers (trust driven information) both in harmony with the extant research.

6.1 LIMITATIONS & FUTURE WORK

One limitation of our approach is that we use multiple non-linear models for analysis that caused burden of jointly estimating the productivity model and simultaneously estimating the models for all job search modes. Both joint and simultaneous estimation of job outcomes require more sophisticated econometric modeling and are left for future extension of this work.

It has been shown that individuals are impatient while being unemployed and are assumed to be willing to work at lower wage (DellaVigna and Paserman 2004), but for simplicity we assumed the reservation wage to be equal to the wage received during the last employment term. This would reduce the computed utility from employment for all individuals but we believe that the user random effect should account for this difference because the difference should be dependent on various user characteristics.

To extend and strengthen the current findings we need to collect more data and possibly longitudinal data to use lag as an instrument and to account for various endogeneity issues. Additionally, we plan to jointly estimate the job outcomes across each search mode and use the non linear offer probability function to estimate the individual productivities. Search allocation and job outcomes from search approaches within online social networks could use further analysis. In summary, this study shows that the online social networks play a significant role in the job search by unemployed professionals. Although there are some limitations because of survey data, we have presented a framework for analyzing social capital for labor market and believe that future work should consider the approach presented here.

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8 REFERENCES

Aral, Sinan, Lev Muchnik, and Arun Sundararajan. 2009. "Distinguishing Influence-based Contagion from Homophily-driven Diffusion in Dynamic Networks." *Proceedings of the National Academy of Sciences* 106 (51) (December): 21544–21549.

Blau, David M., and Philip K. Robins. 1990. "Job Search Outcomes for the Employed and Unemployed." *The Journal of Political Economy* 98 (3) (June): 637–655.

Bloemen, Hans G. 2005. "Job Search, Search Intensity, and Labor Market Transitions an Empirical Analysis." *The Journal of Human Resources* 40 (1) (January 1): 231–269.

Bortnick, Steven, and Michelle Ports. 1992. "Job Search Methods and Results: Tracking the Unemployed, 1991." *Monthly Labor Review* 115 (12): 29.

Bradshaw, Thomas. 1973. "Jobseeking Methods Used by Unemployed Workers." *Monthly Labor Review (pre-1986)* 96 (000002): 35.

Van den Bulte, Christophe, and Gary Lilien. 2001. "Medical Innovation Revisited: Social Contagion Versus Marketing Effort." *The American Journal of Sociology* 106 (5): 1409–1435.

Burdett, Kenneth. 1977. *A Dynamic Theory of Individual Labor Supply*. University of Wisconsin, Institute for Research on Poverty. http://books.google.com/books?id=2CQIAAAAIAAJ.

Burt, Ronald. S. 1995. *Structural Holes: The Social Structure of Competition*. Harvard University Press. http://books.google.com/books?id=FAhiz9FWDzMC.

Calvó-Armengol, Antoni, and Matthew O Jackson. 2004. "The Effects of Social Networks on Employment and Inequality." *American Economic Review* 94 (3): 426–454. doi:10.1257/0002828041464542.

Coleman, James, Elihu Katz, and Herbert Menzel. 1957. "The Diffusion of an Innovation Among Physicians." *Sociometry* 20 (4) (December): 253–270.

DellaVigna, Stefano, and M. Daniele Paserman. 2004. *Job Search and Impatience*. Working Paper. National Bureau of Economic Research. http://www.nber.org/papers/w10837.

Durlauf, Steven N. 2002. "On The Empirics Of Social Capital*." *The Economic Journal* 112 (483): F459–F479.

Economides, Nicholas, and Charles Himmelberg. 1995. "Critical Mass and Network Evolution in Telecommunications." In *Toward a Competitive Telecommunication Industry: Selected Papers from the 1994 Telecommunications Policy Research Conference*, ed. G. W. Brock, 47. Lawrence Erlbaum Associates. http://books.google.com/books?id=HkevyvgMYEgC.

Ellison, Nicole B., Charles Steinfield, and Cliff Lampe. 2007. "The Benefits of Facebook 'Friends:' Social Capital and College Students' Use of Online Social Network Sites." *Journal of Computer-Mediated Communication* 12 (4): 1143–1168. doi:10.1111/j.1083-6101.2007.00367.x.

Garg, Rajiv, Michael D Smith, and Rahul Telang. 2011. "Measuring Information Diffusion in an Online Community." *Journal of Management Information Systems* 28 (2): forthcoming.

Goldenberg, Jacob, Barak Libai, and Eitan Muller. 2001. "Talk of the Network: A Complex Systems Look at the Underlying Process of Word-of-Mouth." *Marketing Letters* 12 (3) (August 1): 211–223.

Granovetter, Mark. 1973. "The Strength of Weak Ties." *The American Journal of Sociology* 78 (6) (May): 1360–1380.

———. 1983. "The Strength of Weak Ties: A Network Theory Revisited." *Sociological Theory* 1: 201–233.

———. 1995. *Getting a Job: A Study of Contacts and Careers*. University of Chicago Press. http://books.google.com/books?id=R7-w4BLg7dAC.

———. 2005. "The Impact of Social Structure on Economic Outcomes." *The Journal of Economic Perspectives* 19 (1) (January 1): 33–50.

Hempel, Jessi. 2010. "How LinkedIn Will Fire up Your Career." *FORTUNE Magazine*, March 25. http://money.cnn.com/2010/03/24/technology/linkedin_social_networking.fortune/.

Holzer, Harry J. 1988. “Search Method Use by Unemployed Youth.” *Journal of Labor Economics* 6 (1) (January): 1–20.

Katz, Elihu, and Paul F Lazarsfeld. 1955. *Personal Influence; the Part Played by People in the Flow of Mass Communications*. http://books.google.com/books?id=PgWxAAAAIAAJ&dq=%22Personal+Influence%3B+the+Part+Played+by+People+in+the+Flow+of+Mass+Communications%22&lr=&source=gbs_book_other_versions_r&cad=2.

Krackhardt, David. 1992. “The Strength of Strong Ties: The Importance of Philos in Organizations.” In *Networks and Organizations: Structure, Form,and Action*, 216–239. Harvard Business School Press.

———. 1998. “Endogenous Preferences.” In *Debating Rationality: Nonrational Aspects of Organizational Decision Making*, ed. Jennifer J. Halpern and Robert N. Stern. ILR Press. http://books.google.com/books?id=JZjWh5T5_7YC.

Kuhn, Peter, and Mikal Skuterud. 2004. “Internet Job Search and Unemployment Durations.” *The American Economic Review* 94 (1) (March 1): 218–232.

Lin, Nan. 1999. “Social Networks and Status Attainment.” *Annual Review of Sociology* 25 (1): 467–487.

Mansfield, Edwin. 1961. “Technical Change and the Rate of Imitation.” *Econometrica* 29 (4) (October): 741–766.

Manski, Charles. 1993. “Identification of Endogenous Social Effects: The Reflection Problem.” *The Review of Economic Studies* 60 (3) (July): 531–542.

McPherson, Miller, Lynn Smith-Lovin, and James M. Cook. 2001. “Birds of a Feather: Homophily in Social Networks.” *Annual Review of Sociology* 27: 415–444.

Merton, R. K. 1968. *Social Theory and Social Structure*. Free Press. http://books.google.com/books?id=dyqZOcux9o0C.

Montgomery, James D. 1992. “Job Search and Network Composition: Implications of the Strength-Of-Weak-Ties Hypothesis.” *American Sociological Review* 57 (5) (October): 586–596.

Mortensen, Dale T. 1986. “Job Search and Labor Market Analysis.” In , Volume 2:849–919. Elsevier. http://www.sciencedirect.com/science/article/B7P5V-4FDF0FK-T/2/afc895b93abf2a37fd684c053693c8ec.

Mouw, Ted. 2003. “Social Capital and Finding a Job: Do Contacts Matter?” *American Sociological Review* 68 (6) (December 1): 868–898.

———. 2006. “Estimating the Causal Effect of Social Capital: A Review of Recent Research.” *Annual Review of Sociology* 32 (1): 79–102.

Petersen, Trond, Ishak Saporta, and Marc-David L. Seidel. 2000. “Offering a Job: Meritocracy and Social Networks.” *The American Journal of Sociology* 106 (3) (November): 763–816.

Rosenbaum, James E., Stefanie DeLuca, Shazia R. Miller, and Kevin Roy. 1999. “Pathways into Work: Short- and Long-Term Effects of Personal and Institutional Ties.” *Sociology of Education* 72 (3) (July): 179–196.

Valente, Thomas W. 2003. “Diffusion of Innovations.” *Genetics in Medicine* 5 (2): 69.

Valenzuela, Sebastián, Namsu Park, and Kerk F. Kee. 2009. “Is There Social Capital in a Social Network Site?: Facebook Use and College Students’ Life Satisfaction, Trust, and Participation1.” *Journal of Computer-Mediated Communication* 14 (4): 875–901. doi:10.1111/j.1083-6101.2009.01474.x.

Verbrugge, Lois M. 1979. “Multiplexity in Adult Friendships.” *Social Forces* 57 (4) (June 1): 1286–1309.